AI-Augmented Annotation Tool for Education of Histopathology

An Educational and Domain-Expert Perspective

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Abstract

Effective teaching of complex and specialized subjects, such as histopathology, requires more than traditional methods, which often lack interactivity and personalization necessary for deep understanding. The integration of artificial intelligence (AI) into educational tools opens new possibilities for enhancing the learning process through adaptive support and interactive feedback.

We present an AI-assisted annotation tool for histopathology education, designed to balance automated assistance with user control while fostering critical thinking and expert oversight. Our system incorporates manual editing, partially AI-driven suggestions, and Wizard-of-Oz simulations to explore advanced tutoring functions. Key features, including contextual textual hints, visual overlays, interactive learning cards, and curated study materials, aim to enhance diagnostic training by providing targeted guidance and reinforcing key morphological concepts.

Through an iterative, user-centered design, we analyze how AI-powered supportive functions influence the accuracy and efficiency of histopathological image annotations among students and whether these features can aid laypersons in grasping fundamental histopathological principles. By evaluating the impact of these AI-driven explanations and interactive modules, we aim to identify strategies that minimize cognitive load, improve retention, and optimize the integration of AI in medical education.

Our findings contribute to the development of AI-enhanced educational tools that support deep learning, improve diagnostic skills, and create a scalable, adaptable framework for medical training. The system is now prepared for extensive student-based evaluation to assess its effectiveness in fostering a deeper understanding of histopathology and its broader implications for AI integration in education.

Keywords: AI in Medicine, Histopathology, Educational Tools, Human-AI Interaction

1 Introduction

Histopathology education often involves time-intensive manual processes with physical slides, limiting immediate feedback for students [13, 5]. Traditional resources, including textbooks and static images, fail to fully address the need for interactive and personalized guidance [9]. To bridge this gap, we developed an annotation tool that combines partial AI suggestions with a flexible user interface, aiming to help novices understand fundamental tissue structures while allowing domain experts to refine suggestions. Additionally, we use Wizard-of-Oz prototyping for certain advanced tutoring features, enabling us to rapidly test the value of AI-like explanations and learning modules before committing to fully automated solutions.

The following sections explore the various aspects of our approach. Section 2 discusses the motivation behind our work and related research in AI-assisted histopathology annotation, emphasizing the limitations of existing tools and the need for interactive educational systems. Section 3 describes our design approach, detailing the user-centered methodology we employed, including the Double Diamond framework and iterative prototyping to ensure usability and effectiveness and focuses on the implementation details of our system that we describe in section 4, covering AI-assisted annotations, interactive learning modules, and the integration of study materials. Section 5 presents the results of preliminary testing with domain experts, highlighting key usability insights, the impact of AI-supported functions on student learning, and necessary refinements. Finally, Section 6 outlines our conclusions and future research directions, including planned large-scale evaluations with medical students to further assess the tool's effectiveness in histopathology education.

2 Motivation and Related Work

Contemporary tools such as QuPath or DeePathology Studio [11] offer semi-automated histopathology annotation but lack explicit educational functions [12]. Our motivation is to provide an environment where students can practice labeling and interpreting complex tissues with real-time feedback [1, 7]. We also seek to accommodate experienced teachers, who need easy ways to review student work, add clarifications, and control which AI hints are shown. Research on user experience in medical education has shown that interactive modules, immediate hints, and domain-focused explanations can significantly enhance learning [8]. However, trust calibration is also critical: novices might over-rely on AI if they are unaware of its limitations, while experts might dismiss potentially helpful suggestions if the system is perceived as opaque or inflexible [6] .

Contemporary histopathology teaching is typically structured around lectures covering morphological theory, followed by hands-on lab sessions in which students examine physical slides under a microscope. Although this setup is effective for building practical skills, it also introduces logistical challenges. Large class sizes often mean students must share equipment, and teachers or lab assistants cannot always offer prompt one-on-one assistance. Many novices hesitate to ask repetitive questions, which can leave misunderstandings unaddressed. Even in institutions adopting digital pathology, the focus may remain on generic annotation tools that do not prioritize educational needs [4].

3 Design Methodology

Our design approach followed an iterative, user-centered philosophy structured by the Double Diamond methodology [3]. This framework allowed us to alternate between phases of broad exploration and targeted solution development, ensuring that our final tool would closely address the practical needs of histopathology students and educators. Figure 1 illustrates the overall process, comprising discovery, definition, development, and iterative refinement.

In the *discovery* phase, we conducted interviews and observational studies with histopathology professors, students, and collaborating IT experts [4, 7]. These sessions revealed recurring challenges: a lack of contextualized feedback when examining tissue samples, difficulties in recognizing fine morphological details, and insufficient support for large-scale studies or repetitive practice. We also noted that many novices quickly disengage if they do not receive interactive, immediate guidance, whereas experts demand higher-level controls to manage AI outputs and validate student progress.

Moving into the *definition* phase, we synthesized these findings into clear objectives: provide partial AI assistance that does not overshadow critical thinking, facilitate efficient teacher oversight, and adapt to varying competency levels. Since we wanted to validate early design concepts before implementing complex machine learning algorithms, we employed Wizard-of-Oz prototyping. This approach allowed us to simulate AI-like behaviors (e.g., hints or auto-detected areas) via human intervention, rapidly iterating on interface elements and user flows.

The *development* phase produced a functional prototype, which combined basic annotation capabilities with simulated AI suggestions. We conducted initial usability testing with an IT expert working alongside domain specialists, who noted excessive cognitive load for first-time users and unclear signposting of the AI's rationale. Guided by these observations, we refined the user interface to be more intuitive, incorporating clearer icons and prominent feedback cues to reduce confusion. Additionally, we introduced interactive educational elements to better integrate theoretical learning with practical annotation tasks. During a second cycle of feedback from a histopathology professor, we discovered that certain features, like saliency maps or a point-and-click auto-annotation mode, were less beneficial from a pedagogical standpoint, as they either offered minimal time savings or undermined manual skill development. Consequently, we removed or downscaled those features, intensifying our focus on explainable suggestions and user-driven annotation.

Finally, in the *refinement* phase, we consolidated the interface changes and further aligned the system with educational needs. Our iterative tests confirmed that partial AI assistance can be valuable if transparently communicated and balanced with manual control. Moreover, we validated the need for well-structured study materials accessible from within the annotation interface, so that students remain in context while deepening their theoretical knowledge. From these methodological insights, we shaped a system that simultaneously supports novices and experts, emphasizing clarity, interactivity, and domain-relevant feedback.

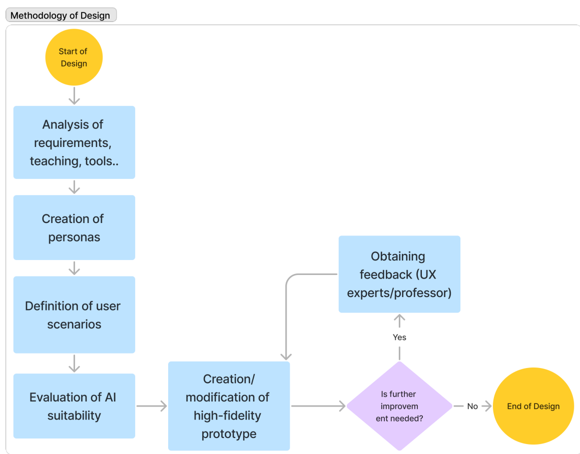

Figure 1: Flowchart diagram representing our overall design methodology based on the Double Diamond approach.

4 Proposed System Features

Building on the iterative process described above, we identified several core functionalities that address the distinct needs of students and teachers in histopathology education. Our tool features a *task-based interface* (Figure 2), which presents structured exercises such as quizzes, diagnostic challenges, and self-guided annotation tasks. This design ensures that students can focus on systematically refining their morphological recognition skills while receiving real-time support.

Central to the student experience is **AI-assisted annotation**, where the system highlights potential areas of interest for further inspection. Crucially, users maintain full control over the final labels, thus avoiding over-reliance on automated outputs. To aid in comprehension, we integrated **textual hints and visual overlays** (Figure 3), which provide targeted clues explaining key structures or patterns. These overlays are deliberately minimal so as not to replace the student's own diagnostic efforts. They also emphasize transparency in how suggestions are derived, aligning with the need for clear, explainable AI in medical education.

To reinforce theoretical knowledge, we incorporated **interactive learning cards** that appear contextually during annotation (Figure 9). These brief pop-ups compare normal and abnormal histological samples or pose short diagnostic quizzes. Early trials indicated that students benefit from immediate access to reference materials without leaving the annotation workspace. Thus, **integrated study materials** (Figure 4), such as curated tutorials, reference atlases, and lecture notes, are accessible directly within the tool. This design choice helps learners relate morphological theory to specific annotation tasks, maximizing both engagement and retention.

Figure 2: Prototype of the task selection screen. Students can navigate among quizzes, diagnostic challenges, or self-annotation tasks.

Beyond these core student-facing elements, we introduced a **study materials window** (Figure 5), where learners can instantly access supplemental resources, books, or relevant online links. This pop-up format centralizes external references, sparing users from switching platforms mid-task and allowing them to cross-check morphological features against authoritative sources. Students at any level can thus enrich their theoretical grounding whenever they encounter unfamiliar structures.

We further explored specialized AI functionality by implementing **automated blood vessel detection**, as illustrated in Figure 6. When enabled, the system attempts to highlight vascular structures on the slide. While this feature remains under continuous development, its primary goal is to reduce repetitive manual marking and guide learners toward regions warranting closer inspection. Students still confirm each annotation, preserving the educational value of hands-on identification.

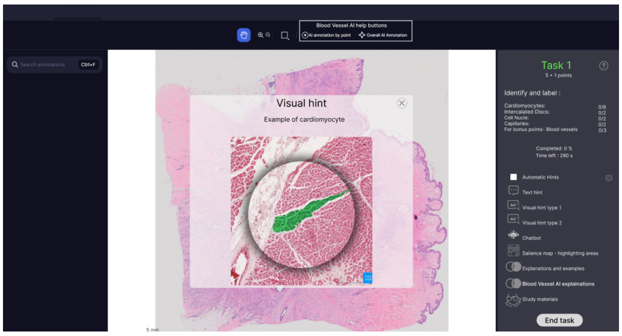

Figure 3: Prototype of the visual hints module. Minimal overlays guide the user's attention without overshadowing their own critical reasoning.

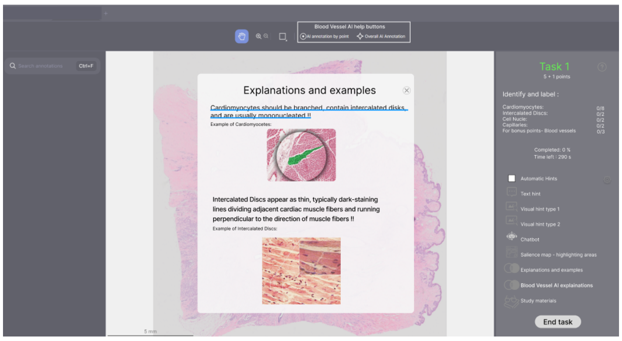

Figure 4: Example-based study module (another prototype view). Students can switch between normal and abnormal tissue illustrations.

Since learners vary in their familiarity with histopathology, we introduced a **difficulty setting** (Figure 7) that adjusts the level of hints, overlays, and automated suggestions. Total beginners, labeled as "Layman," can receive frequent guidance, whereas more advanced users may opt to minimize AI prompts and rely on their own diagnostic reasoning. This flexible setup prevents novices from becoming overwhelmed while providing seasoned students an opportunity to focus on finer diagnostic nuances.

In parallel, we developed a **teacher oversight module** that consolidates class-wide progress and offers a high-level view of individual student performance (Figure 8). Educators can create tasks with specific objectives, enable or disable certain AI features, and add clarifications or tips directly in the annotation interface. This capacity to adjust system behavior on a per-assignment basis ensures that novices remain supported, while advanced users can

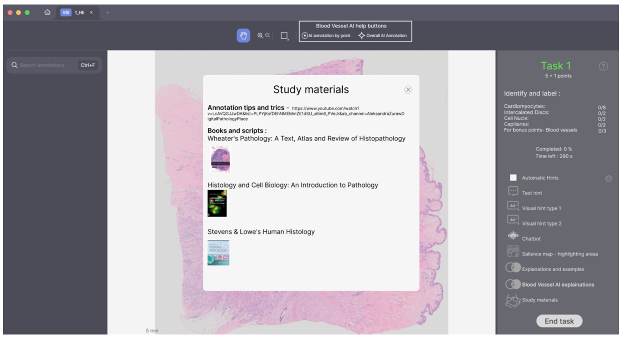

Figure 5: Study materials window providing quick-reference tips and recommended readings within the same interface.

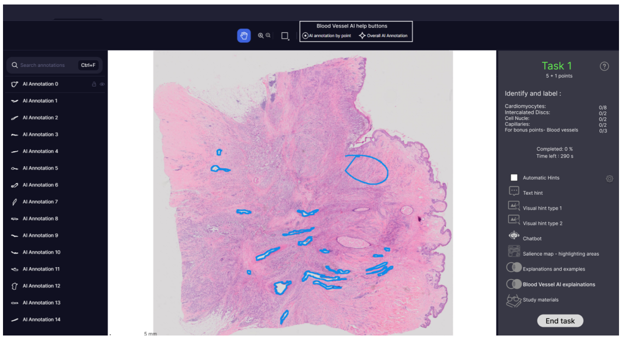

Figure 6: Prototype of AI-assisted blood vessel annotation. Users can refine each suggested label to ensure accuracy.

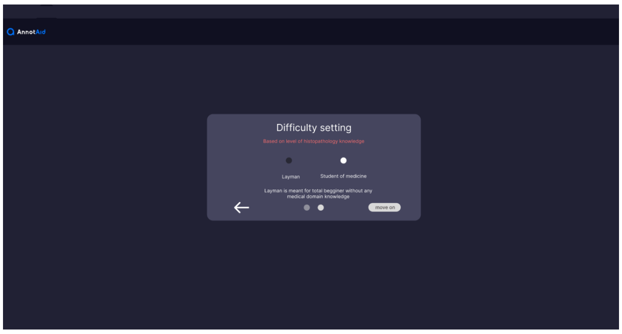

Figure 7: Difficulty setting dialogue, allowing each user to calibrate the degree of AI assistance based on their expertise.

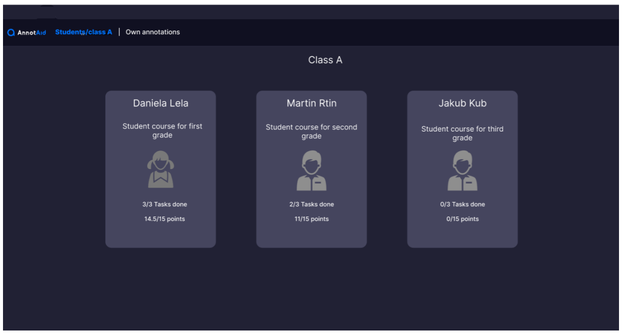

Figure 8: Teacher module interface, presenting a high-level view of student progress and enabling task-specific AI settings.

be challenged more rigorously. Although teachers cannot directly alter the AI's underlying outputs, they can decide how prominently automated suggestions feature in a given exercise, preserving manual practice where needed.

Lastly, we reinforced the importance of **adaptive learning levels** by combining these functionalities—study materials, automated hints, difficulty settings, and teacher oversight—into a cohesive environment. By calibrating the intensity of AI involvement, the system fosters both self-driven exploration for advanced students and scaffolded support for novices. Throughout our iterative evaluations, we found that transparency in AI suggestions and a balanced level of automation are key to promoting deeper morphological comprehension rather than shallow acceptance of computational outputs. The following section discusses how these features performed during preliminary testing and highlights additional refinements guided by expert feedback.

5 Results and Discussion

Our iterative evaluation of the AI-assisted histopathology annotation tool yielded valuable insights into user needs, system usability, and educational effectiveness. We conducted two rounds of user-centered testing — first with an IT expert collaborating with histopathologists to focus on general usability, followed by a domain expert (a professor of histopathology) focusing on domain-specific utility. The findings from these two iterations guided successive refinements of the tool's design. In the first iteration, an IT expert working alongside histopathologists examined the prototype to identify fundamental usability issues and primary user needs. The evaluation revealed several challenges that could hinder effective use of the annotation tool. Notably, the expert observed that cognitive load was high for first-time users due to a complex interface and lack of guidance, and that users might struggle to interpret the AI's annotations without additional context or explanations. The need for intuitive design and better support for users' understanding of the AI emerged as critical considerations. Based on these observations, the IT expert recommended a set of targeted design improvements. Visual interface enhancements were proposed to make the tool more intuitive: for example, clearer icons and overlays to guide users through annotation steps, and layout adjustments to highlight important actions. The expert also suggested integrating interactive educational flashcards(learning cards)into the system. These flashcards would periodically introduce or reinforce key histopathological concepts (Figure 9), helping users connect the AI's annotations with underlying theory. In

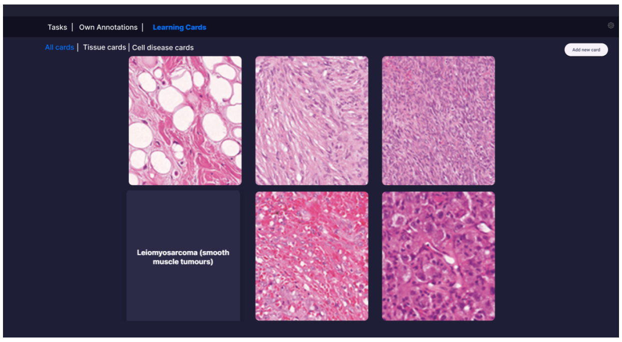

Figure 9: Prototype of the educational learning cards module, which presents concise comparative examples or short quizzes.

addition, a strong emphasis was placed on incorporating explainable AI (XAI) features to address the transparency of AI decisions [2]. We implemented these recommendations in the next prototype, adding visual guidance elements, a flashcard module for on-the-fly learning, and initial XAI components for better transparency [10].

The second iteration of testing was conducted with a professor of histopathology, whose feedback focused on the tool's effectiveness in an authentic educational and diagnostic context. This domain expert validated many of the improvements introduced in the first iteration. She reported that the updated interface with clear visual cues significantly reduced the initial learning curve for using the tool. The inclusion of flashcards was found to be beneficial in reinforcing domain knowledge. Moreover, the expert noted that the explainable AI features fostered greater trust in the system.

Despite these positive outcomes, the histopathology professor identified certain AI-driven functionalities that were not effective or could be counterproductive. In particular, two features were flagged: saliency maps and the point-and-click AI annotation mode. The saliency maps were often misaligned with expert focus or too abstract to provide meaningful insight. The point-and-click annotation feature did not save time and could degrade the learning experience—users might become passive, or the AI's suggestion would still require extensive correction. Given that the goal is to train human expertise, an overly eager automation of the annotation task was seen as undermining the educational value of manual practice.

As a result of this feedback, we removed the saliency maps and the point-and-click automation in the subsequent version of the system. Instead, we concentrated on improving features that actively engage the user and promote understanding. The domain expert strongly advocated for better AI transparency in more pedagogically useful forms, such as textual explanations aligning with expert reasoning. She also emphasized the potential of personalized learning materials, recommending that the tool adapt to each user's performance—tracking common mistakes and offering tailored support.

Summarizing both iterations, the first phase focused on refining usability based on the recommendations of an IT expert who collaborated with histopathologists. This led to a more intuitive interface, better user guidance, and the introduction of learning elements like flashcards and AI explainability. The second phase, validated by a histopathology professor, confirmed the usefulness of these improvements while highlighting the need for further refinements, particularly in eliminating ineffective AI functionalities and improving transparency. The feedback from both perspectives ensured that the system became both technically robust and aligned with real-world educational needs.

Our findings demonstrate that educational technology benefits greatly from cross-disciplinary collaboration. By incorporating principles of user experience design into a domain-specific tool, we created a system that not only assists annotations but also actively facilitates learning. This underscores that user-centered design and domain-driven content are both critical in developing effective AI-based learning tools.

Our results also highlight the role of AI explainability and transparency in medical training. The positive reception of the XAI features suggests that explainable AI can serve as a teaching assistant, articulating the "why" behind a decision and helping students grasp complex histopathological reasoning. Features that are not easily interpretable or that encourage passivity may hinder learning. Thus, transparency must be implemented in a pedagogically meaningful way—providing explanations that mirror expert reasoning rather than through opaque visualizations.

Another significant implication is the importance of adaptability and personalization in medical education. The domain expert's recommendation for personalized learning materials suggests that AI-assisted tools can be leveraged to deliver adaptive learning experiences. By adding targeted flashcards, hints, or practice cases addressing specific errors, the tool can reinforce learning where it is most needed.

Finally, the iterative development and testing process itself holds lessons for AI deployment in medical training. The collaboration between IT specialists and medical experts ensured that the final system was both technically effective and aligned with end-user workflows. This two-pronged evaluation strategy could be a model for developing similar AI-assisted educational tools in other fields of medicine.

In conclusion, our AI-assisted histopathology annotation system has evolved into a powerful educational platform that blends AI-driven assistance with expert-driven learning strategies. The final prototype is now fully prepared for final testing with medical students, where it will undergo large-scale evaluation to measure its impact on histopathological skill acquisition, learning efficiency, and diagnostic confidence.

6 Conclusion and Future Directions

We have described an annotation system tailored to histopathology education, merging partial AI-driven highlights with rich learning materials, teacher-labeled clarifications, and a student-facing mode designed to foster careful morphological analysis. An iterative development cycle, grounded in interviews and pilot tests, proved essential for refining interface design and ensuring novices do not overly depend on automated cues.

Future work involves expanding formal evaluations to larger groups of students at various training stages, measuring annotation accuracy, speed, and retention before and after extended tool usage. We also plan to integrate a fully trained machine learning backend in place of Wizard-of-Oz simulations, incorporating advanced interpretability methods so learners can see why a particular region was flagged. Ultimately, our vision is to seamlessly blend human expertise and selective AI support, ensuring that histopathology trainees gain deeper, more consistent practice without sacrificing the structured teaching that remains at the heart of medical education.

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